Comparison between Representer Method and EnKF for flow in porous media applications

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Introduction

Data assimilation is a fairly new technique for estimating the uncertain parameters in the reservoir models. Here the two different assimilation methods: variational one - the Representer Method, and the sequential one - the Ensemble Kalman Filter, are compared based on their ability to estimate the permeability field in an academic example of a 2D 2-phase (oil - water) reservoir model with one water injector in the middle of a field and four oil producers in the corners of a field. In case the reservoir model and observation model are linear and the uncertainties can be described by Gaussian random variables, both methods should give the same estimate. The reservoir model, however, is nonlinear and the uncertainties (first two moments) are obtained here based on 1000 ensemble members generated from a training image.

Representer Method (RM)

The Representer Method is a variational approach:

- the gradient is calculated with adjoint method,
- the uncertainty in parameters is captured in the covariance matrix,
- the parameter field is reparameterized in terms of data - driven basis functions called representers.

The optimal solution for parameters **θ** is written as linear combination of representer functions **Θ** weighted by representer coefficients **b** plus the prior knowledge $\boldsymbol{\theta}_p$,

$$\boldsymbol{\theta} = \boldsymbol{\theta}_p + \sum_{j=1}^{N_m} b_j \boldsymbol{\Theta}_j$$

The number of representers equals the number of measurements N_m . In this way, instead of estimating a huge number of original parameters, one estimates only the representer coefficients limiting the number of unknowns to the number of measurements used in data assimilation. This method uses the optimal parameterization by reducing the number of estimation parameters while still providing a solution to full inverse problem.

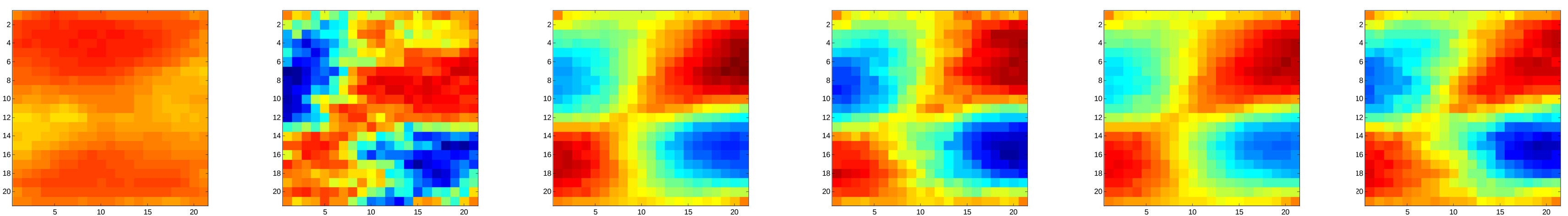
Ensemble Kalman Filter

The Ensemble Kalman Filter is a Monte Carlo approach:

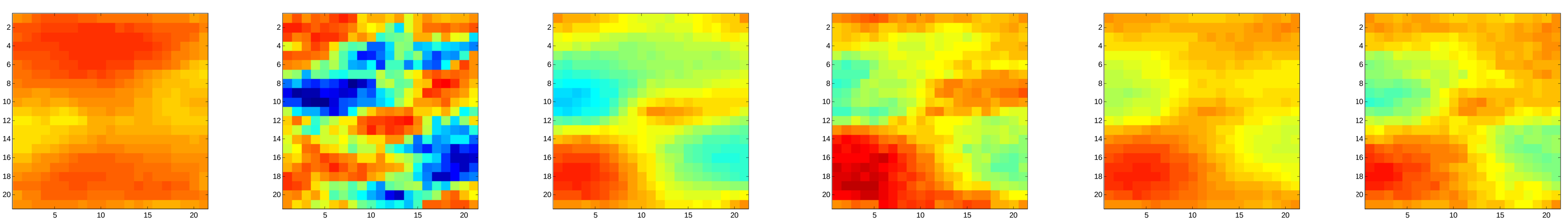
- the probability density of the parameter estimate is represented by the ensemble of possible parameter fields: $\boldsymbol{\theta}_1$, $\boldsymbol{\theta}_2$, …, $\boldsymbol{\theta}_N$,
- each ensemble member is assumed to be a single sample out of a distribution of the true parameter field,
- the statistical moments are approximated with sample statistics,
- consists of two steps: forecast step, where the ensemble members are propagated with reservoir simulator, and analysis step, where the initial mean and covariance are updated every time measurements become available,
- it does not require the implementation of the linear tangent model, because the ensemble members are propagated through the original nonlinear model,
- it requires a big number of ensemble members to properly describe the prior uncertainty in the parameters, which becomes impractical for the applications with large amount of parameters to be estimated (10^6-10^7 in reservoir applications),
- the proper knowledge of statistics is important.

Number of measurements and measurement error

The estimates of two permeability fields obtained with both methods for different number of measurements used in the estimation process and different measurement error statistics are compared here. The EnKF uses 80 ensemble members chosen randomly form a set of 1000 ensemble members. First picture shows the prior permeability field, second - the true permeability field, third to sixth - the estimates obtained with Representer Method and EnKF using 10 (or 55) data points and small and big data errors, respectively.



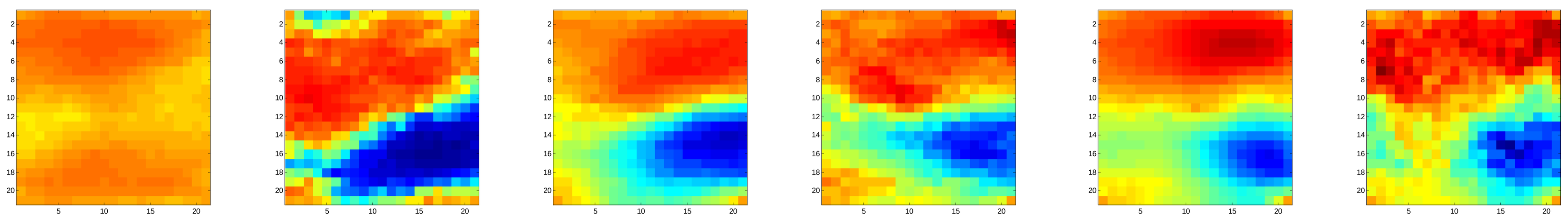
In the first example the production data (bottom hole pressures, flow rates gathered from five wells located in the middle and in four corners of a field) are very informative and a good estimate is obtained using only 10 of them. Adding new data points doesn't significantly improve the estimates. The updates obtained with RM and EnKF are comparable. The magnitude of measurement errors doesn't seem to play a role for this example. The estimates obtained with big model errors lose a bit of resolution especially in the lower permeability zones, but are good enough for predictions.

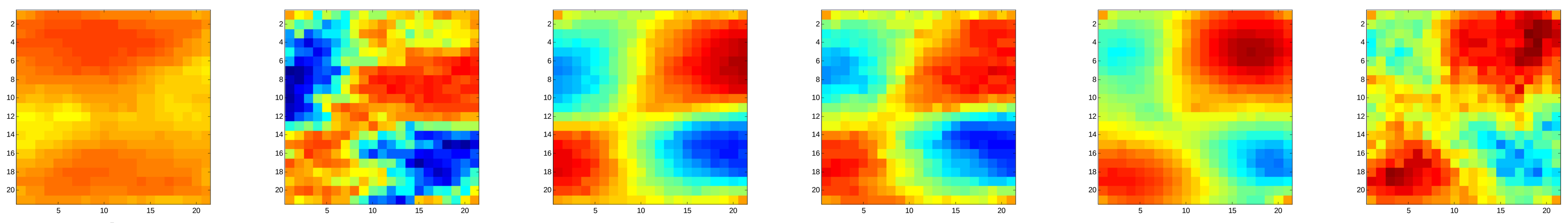


In the second example the production data doesn't contain enough information to be able to recover the underlying permeability field. Adding extra data points (55 measurements instead of 10) helps to improve the estimate for both methods. Because of the complexities present in the true permeability field, the updates obtained with RM and EnKF are not acceptable to be used for future predictions. Extra measurements (seismic data) gathered at different spatial locations than production data would help to further constrain the reservoir model.

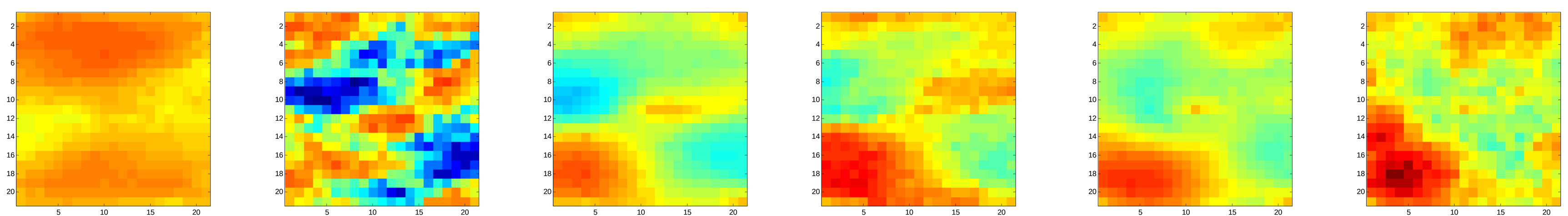
Wrong prior statistics for parameters being estimated

The estimates of three permeability fields obtained with both methods with the wrong prior information used in the estimation process are compared here. First picture shows the prior permeability field, second - the true permeability field, third to sixth - the estimates obtained with Representer Method and EnKF using correct and wrong prior information, respectively.





In the first two examples the production data contain enough information to turn the data assimilation algorithms in the right direction. Even if the wrong prior knowledge is used, the algorithms are able to recover main features present in the true permeability fields. Their ability to recover details increases as the number and quality of data used increases.



In case of more complex structures present in the true permeability field, the use of a wrong prior knowledge diminishes estimation results.

Conclusions

The Representer Method and the Ensemble Kalman Filter are powerful data assimilation methods that allow one to combine the prior knowledge about the quantity being estimated with the knowledge contained in the measurement set to arrive at the estimate which resembles the 'truth' and can be used for predictions. The examples presented here show, however, that special care must be taken when using both algorithms for nonlinear estimation. For our 2D nonlinear reservoir model both algorithms seem to perform in similar way. They are sensitive to the quality of prior information used in the assimilation and tend to be biased in that direction. If enough data is used, however, this problem can be partially overcame. The estimates obtained with Representer Method and Ensemble Kalman Filter are comparable and give similar results for the future performance of a reservoir. Both algorithms failed to estimate more complex structures present in one of the permeability fields. In this case production data alone are not informative enough, thus the other types of data (time –lapse seismic data) should be incorporated into data assimilation scheme to further constrain the estimate.

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